An improved bias correction scheme based on comparative precipitation characteristics

Kue Bum Kim[1*], Michaela Bray[2], Dawei Han[1]

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* Corresponding author: kk12496@bristol.ac.uk

[1] Water and Environmental Management Research Centre, Department of Civil Engineering, University of Bristol, Bristol, UK
(Kue Bum Kim, email: kk12496@bristol.ac.uk, Dawei Han, email: d.han@bristol.ac.uk)
[2] Hydro-Environment Research Centre, School of Engineering, Cardiff University, Cardiff, UK

Abstract

Bias correction is a necessary post-processing procedure in order to use Regional Climate Model (RCM) simulated local climate variables as the input data for hydrological models due to systematic errors of RCMs. Most of present bias correction methods adjust statistic properties between observed and simulated data based on calendar periods, e.g., month or season. However, this matching statistic is only a necessary condition, not a sufficient condition, since temporal distribution of the precipitation between observed and simulated data is ignored. This study suggests an improved bias correction scheme which considers not only statistical properties but also the temporal distribution between the time series of observed and modelled data. The ratio of the observed precipitation to simulated precipitation is used to compare the behaviour between the observed and modelled precipitation data and three criteria are proposed when dividing bias correction periods: 1) over/under estimation of precipitation, 2) stability of precipitation ratio and 3) oscillation of precipitation ratio. The results show that the output of the proposed bias correction method follows the trend of the observed precipitation better than that of the conventional bias correction method. This study indicates that temporal distribution should not be ignored when choosing a comparison period for bias correction. However, the study is only a preliminary attempt to address this important issue and we hope it will stimulate more research activities to improve the methodology. Future efforts on several unsolved problems have been suggested such as how to find out the optimal group number to avoid the overfitting and underfitting conditions.

Keywords: bias correction, rainfall characteristic, temporal distribution, quantile mapping

1. Introduction

From the hydrological cycle and water resources perspective, the impacts of climate change are of increasing interest to water resources managers (Compagnucci *et al.*, 2001; Bates *et al.*, 2008). Numerous studies have been done to assess the impacts of climate change on water resources which are based on climate variables from Global Climate Models (GCMs) and water resources models (Fung *et al.*, 2011). However, because of the relatively low spatial resolution (100-250km) of GCMs, Regional Climate Models (RCMs) are widely used for regional impact studies at catchment scale (25-50km) climate variables (Fowler *et al.*, 2007; Qin *et al.*, 2007). Although RCMs are able to simulate local climate at a finer grid, it is well known that outputs from RCMs cannot be used as direct input data for hydrological models due to systematic errors (i.e., biases) and need post processing of the model outputs to remove biases (Hansen *et al.*, 2006; Sharma *et al.*, 2007; Christensen *et al.*, 2008). Research has shown that typical systematic model errors of RCMs are shown as misestimation (over or under) of climate variables, incorrect seasonal variations of precipitation (Christensen *et al.*, 2008; Terink *et al.*, 2009; Teutschbein and Seibert, 2010) and simulation of too many wet days of low intensity rainfall (drizzle effect) than the observed (Ines and Hansen, 2006).

Several studies on bias correction methodology have been done recently from simple linear scaling to sophisticated quantile mapping method (Piani *et al.*, 2010; Chen *et al.*, 2011; Chen *et al.*, 2011; Johnson and Sharma, 2011; Teutschbein and Seibert, 2012). Teutschbein and Seibert (2012) conducted statistical evaluation of four bias correction procedures for precipitation: 1) linear scaling (Lenderink *et al.*, 2007), 2) local intensity scaling (Schmidli *et al.*, 2006), 3) power transformation (Leander and Buishand, 2007; Leander *et al.*, 2008) and 4) distribution mapping method (Déqué *et al.*, 2007; Block *et al.*, 2009; Piani *et al.*, 2010; Johnson and Sharma, 2011; Sun *et al.*, 2011). The linear scaling approach corrects mean values based on the differences between the observed and model data, i.e., it considers bias in the mean, using a correction factor based on the ratio of the long-term mean observed and modelled data. Local intensity scaling is an advanced method which accounts for not only the bias in the mean but also wet day frequencies and wet day intensities. Power transformation adjusts the mean as well as the variance of a precipitation time series. Distribution mapping is to adjust the distribution of model output to that of the observed data using transfer function. The results showed that there was an improvement of the raw RCM precipitation data with all the bias correction methods and that the distribution mapping was found to be the best correction procedure. However, the main weakness of these conventional methods is that they neglect temporal distribution of rainfall characteristics. All the existing bias correction methods are performed on a calendar basis: monthly or seasonal statistic properties are equalised between the modelled and observed climate data. These data grouping may break natural characteristics between the observation data and RCM simulated data and may mix different precipitation features into one segment because rainfall characteristics does not exactly follow monthly or seasonal boundaries. The idea of an improved bias correction method is proposed in this study to resolve this problem in order to match similar rainfall events between the observed and modelled time series data by considering precipitation temporal distributions.

Here, we would like to note that the proposed methodology uses only one climate model and one scenario because the purpose of this study is mainly to illustrate the flaw of the conventional calendar based bias correction method and to suggest the logic for the improved precipitation characteristics based bias correction method.

2. Study Catchment and data

Study area

The Exe catchment is located in the southwest England. The catchment area is 1530 km^2 and its average annual rainfall is 1088 mm. Four major tributaries of River Exe are River Culm, River Barle, River Clyst and River Creedy, and the river flows into the sea via the Exe Estuary on the south coast of England. The main urban areas in the Exe catchment are Exeter, Crediton, Tiverton, Cullompton. Figure 1 shows the overview of the Exe catchment area. In this study the Thorverton catchment (606km^2) which is one of the Exe subcatchment is used. Daily time series of the observed precipitation data over the Thorverton catchment is derived from 5 rain gauges (extracted from the UK Met Office's MIDAS database) using the Thiessen polygon method for the baseline period (1961-1990).

Regional climate model (RCM) data

The climate data used in this research has been generated by HadRM3. HadRM3 is a Met Office Hadley Centre's regional climate model (resolution 25×25km) which is used to produce regional projections of the future climate from the global climate model HadCM3 (Murphy *et al.*, 2009). The RCM data consist of one unperturbed member and 10 perturbed members driven by historical emissions and future emission scenario A1B which assumes a balance between fossil fuels and other energy sources. 31 parameters were selected for this perturbation from the unperturbed member representing cloud, convection, radiation, atmospheric dynamics, boundary layer, land surface and sea-ice. The HadRM3 Perturbed Physics Experiment Dataset (HadRM3-PPE-UK) provides time series data from 1950 to 2100 and the spatial and temporal resolutions are 25km grid in space and day in time respectively. Detailed information about the HadRM3-PPE data can be found at http://badc.nerc.ac.uk/browse//badc/hadrm3/data/hadrm3-ppe-uk. The RCM 25km grid boxes are rotated 0.22^{o} as shown in Figure 1. Here, among 11-member only the unperturbed RCM daily precipitation series for the baseline period 1961~1990 is used in this study and the grid is selected which covers the Thorverton catchment.

3. Methodology

3.1 Statistical bias correction methods

The Gamma distribution is commonly used for rainfall distribution since it can provide a variety of distribution shapes (Wilks, 1990). In this study the two parameter Gamma distribution is applied and its function is as follows:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta};\ x \geq 0;\ \alpha, \beta > 0 \tag{1}$$

where, Γ is gamma function, α is shape parameter, β is scale parameter. Among various bias correction methods the quantile mapping method based on the Gamma distribution is selected for bias correction of the daily RCM simulated precipitation data. The objective is to map the observed and simulated quantiles using their corresponding Gamma distributions. The calendar year is divided into monthly or seasonal segments and bias correction is performed within each segment individually. In this study, bias correction is conducted for each season independently after matching wet day frequency between the observed and RCM simulated precipitation data by modifying the RCM simulated data using a cut-off threshold. Daily Gamma cumulative distribution functions (CDFs) are built from a seasonal period for both observed and RCM simulated precipitation from 1961 to 1990. Figure 2 presents the schematic of the distribution mapping method. First, the value of the RCM simulated daily precipitation is found in the Gamma CDF and the corresponding cumulative probability from the observed Gamma CDF. Then the value of precipitation with the same cumulative probability is searched in the observed Gamma CDF. This value is the corrected value of the RCM simulated precipitation. The equation can be expressed as follows:

$$X_{cor} = F^{-1}\left[F(X_{mod}\ ;\ \alpha_{mod}\ \beta_{mod})\ ;\ \alpha_{obs}\ \beta_{obs}\right] \quad (2)$$

where, F is Gamma CDF, F^{-1} is its inverse function, X_{cor} is the bias corrected data in the baseline period, α and β are shape and scale parameters of the Gamma distribution respectively. The subscript *mod* and *obs* indicate the parameters from the RCM simulated precipitation and observed precipitation.

Usually the RCM simulated precipitation values have a numerous number of days with low precipitation compared with the observed precipitation. Therefore, a cut-off threshold is commonly used to remove low precipitation values in the model output in order to equalise the frequency of wet days between the observed and simulated precipitation before applying the quantile mapping method. After bias correction, the RCM simulated Gamma CDF is shifted to the observed Gamma CDF.

The problem with the bias correction studies so far lies in their boundary selections. Although statistical properties of the corrected data can match those of the observation data after bias correction when performed on the calendar boundary basis, it does not take into account the temporal distribution of the time series data. For hydrological applications, not only statistics but temporal condition should be matched as well. The flaw of the calendar based bias correction is demonstrated in Figure 3. If time series of the observation and RCM simulated data are symmetrical as illustrated in Figure 3, we can see that their rainfall temporal characteristics are considerably different. However when we plot CDFs both the observed and RCM CDF are identical, indicating that no bias correction is needed based on CDF albeit it is required.

Figure 4 illustrates the drawback of the calendar based bias correction. Ideally, similar rainfall events should be corrected with similar CDFs but in most cases rainfall characteristics between the observation data and RCM simulated data do not follow individual seasons exactly. In Figure 4, in the first half of the summer the model overestimates compared with the the observed precipitation while during the second half, the model underestimates the precipitation which means that the bias correction period should be divided in the middle of the summer, and not at the seasonal boundaries, in order not to ignore the variation of rainfall characteristics between the observation data and the RCM simulated data within the summer. Hence, the bias correction period should not be divided by calendar boundaries but by similar rainfall data characteristics. When we perform quantile mapping bias correction, the CFDs can match after correction, even though the uncorrected model data is very poor in time compared with the observed data. For this reason it is not sufficient to judge whether or not bias correction has been done properly based on CDF correction alone.

3.2 Proposed method: Bias correction based on comparative rainfall characteristics

Low pass signal filtering using FFT

The idea of a new bias correction scheme is to group the bias correction period based on the comparative behaviour of the observation and RCM simulated precipitation data. In this study the ratio of the observed precipitation to the model precipitation is selected as the grouping index and its temporal distribution is used to group the data for quantile mapping. Because both the observation and RCM precipitation data have fluctuations (i.e., noisy), which makes it difficult to classify data into groups, it is necessary to eliminate these high frequencies. A low pass filter based on the Fourier Transform is applied to filter out the noise, i.e. high frequency signals from the precipitation data and make the time series smoother to help identifying rainfall features between the observation and RCM data.

The Fourier Transform is used to map signals from the time domain to the frequency domain. The Fourier Transform *F(w)* and inverse Fourier Transform *f(t)* are defined as follows.

$$F(w) = \int_{-\infty}^{\infty} f(t)e^{-iwt}dt \qquad (3)$$

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(w)e^{iwt}dw \tag{4}$$

After the Fourier transform of the data, a variety of filters are explored to smooth the data time series to reduce fluctuations. In this study, the Hamming-window filter is applied as follows.

$$w(n) = 0.54 - 0.46\cos(\frac{2\pi n}{N-1}), \qquad 0 \leq n \leq N\text{-}1 \tag{5}$$

where, N is the length of the filter window.

Grouping based on signal ration between observation and model data

The principle of dividing bias correction periods uses the similarities between the observed and simulated daily mean precipitation for 30 years (1961-1990). The ratio of the observed to simulated precipitation is used to represent the comparative rainfall characteristics. Here, only the ratio of the means is considered as the grouping criterion since our major concern is for water resource management, i.e., the volume of water. However, flood studies are interested in extreme water distribution and in this case, the second (variance) and third (skewness) moment should be considered as well when grouping bias correction periods.

\- Three criteria are used to divide the 360-day calendar year into sub groups in order to match the CDF of the observed and simulated data and to find out their natural and stable boundaries. These are as follows: Firstly, the precipitation ratio of the observed to the model above one or below one, i.e. overestimation or underestimation of precipitation should be treated as the same group respectively. Secondly, stability and sensitivity of the precipitation ratio is considered. The basis of dividing groups is the signal of the data, hence, consistency of the signal with time should be taken into account to check the stability and sensitivity of the group. This is done by making an ensemble of 29-year mean precipitation ratios by removing every year’s precipitation data from 1961 to 1990. The wide range part of this ensemble has been categorised into one group as the precipitation ratio of this group is sensitive and unstable. In addition, an ensemble of 20-year mean precipitation ratios estimated by removing every 10 year precipitation data from 1961 to 1990 are used as well to judge the similarity of the group behaviour. Finally, the period that has similar oscillation has been treated as one group. When the 360-day year calendar is categorised based on these three criteria simultaneously, the created bias correction period boundaries are found not coincided with the calendar seasonal boundaries.

4. Results

4.1 Comparison between RCM data and Observations

To assess the performance of the 11-member RCM data for the baseline period, monthly mean precipitations for the Thorverton catchment have been compared between the RCM data and observation data. Figure 5 shows that the trend is similar but actual values do not match, and there are clearly biases between the observation and climate model during the baseline period. 11 RCMs tend to produce more rainfall than the observed between February and June, but less between August and December. Therefore, the biases exist in time (Figure 5 (left)) and in rainfall intensity (Figure 5 (right)).

4.2 Digital filtering results and grouping based on comparative rainfall characteristics

Figure 6 presents the power spectrum of the observed precipitation data after the Fourier Transform. The amplitude decreases until the frequency is 0.05 and afterward it fluctuates. Hence, 0.05 has been set as the cut-off frequency for both the observation and RCM data. Figure 7(a) shows the signal of the observation and model data after filtering out high frequencies. The 30-year mean precipitation ratio is shown in Figure 7(b) and ensembles of 29-year and 20-year mean precipitation ratios are illustrated in Figure 7(c) and Figure 7(d) respectively. Time series of the precipitation ratio is divided into 5 groups based on three criteria as noted before: over/underestimation, sensitivity and oscillations. Group 1 and Group 2 are the groups which the precipitation ratios are over 1, i.e. underestimating the observed trends, while Group 3 overestimates the observed trends. Group 4 has been classified together as the spread of its precipitation ratio ensemble is wide and unstable. Finally, Group 5 has been categorised as one because the precipitation ratio is over one and oscillations are similar within the group.

4.3 Comparison of bias corrected signal

Comparison of the bias corrected signal for the seasonal based correction and the comparative rainfall characteristic based correction are illustrated in Figure 8. The result of comparison can be considered as a reasonable approach because the numbers of groups are similar, four and five for the seasonal based correction and the comparative rainfall characteristic based correction respectively. For both cases, RCM CDFs are exactly matched with the observation CDFs for every season and every group. As a result an improvement of the raw RCM data is achieved. However, when time series are plotted we can clearly see the problem of the calendar based bias correction (Figure 8(a)). In the summer, during the first third period (June) the model overestimates the observation trends while during the last two-thirds of the period (July, August) the model underestimates the observation trends. Nevertheless, if bias is corrected on seasonal basis using CDFs which are constructed from the summer observation and RCM data from 1961 to 1990, time series of the corrected RCM data does not follow the trend of the observation data as shown in Figure 8(a). This is because data with different comparative rainfall characteristics are treated as one group to build CDFs, hence, the trend of the bias corrected rainfall does not follow the observation data even though the CDFs are matched perfectly after the bias correction. In other words, temporal distribution has been ignored in the grouping. However, when bias correction periods are divided naturally on the basis of comparative rainfall features this problem can be resolved. Figure 8(b) shows that time series of the bias corrected rainfall in the summer is similar to that of the observation data.

5. Discussion and Conclusions

This study proposed a new approach for RCM bias correction which considers the rainfall temporal distribution characteristics and each bias correction group has similar features between the ratio of the observed and simulated data. Conventional bias corrections use calendar boundaries, i.e. monthly or seasonal based correction, and as a result they ignore rainfall characteristics between the observation data and model simulated data. Our results show that the comparative rainfall characteristic bias correction method has the improved results compared with the conventional bias correction methods. This is because the proposed method avoids the mixing of different comparative rainfall characteristics into one segment and the defined bias correction periods are more realistic and appropriate. Quantile mapping, one of the conventional bias correction methods, only uses CDF as a performance indicator and this is not sufficient. It is only a necessary condition, not a sufficient condition, because the CDF temporal features of the rainfall are ignored. Perfectly matched CDFs cannot guarantee a temporal match between the model and observation data.

However the study is only a preliminary attempt to address this important issue and we hope it will stimulate more research activities to improve the methodology with different climatic conditions so that more experience and knowledge could be obtained. Here are some possible problems to be explored further. Firstly, more research is needed to find out how many groups are optimal for bias correction. From the intuition, the more groups we have, the smaller temporal error will be in the bias correction. However, we may come to meet the overfitting issue and there is a question on the well-known trade-off between bias and variance.. This is because smaller temporal error may not mean it is a good bias correction if bias correction fits to noise in the data instead of the underlying signal. Hence, we cannot judge by the temporal error alone. Performance of the overfitted model has the small error for the calibrated data but may have large errors when the model is validated with the unseen data. Cross validation could be a method to resolve this issue and will be explored in the future. The Akaike information criterio (AIC) could be another possible method for choosing the optimal number of bias correction groups. On the other hand, underfitting (i.e., too fewer groups) should also be avoided and be studied simultaneously with the overfitting problem. Secondly, further studies are needed to refine and amend the proposed grouping criteria. Thirdly, it is harder to subdivide individual groups into sub-groups (e.g., 5 groups are used in this study yet some corrected data does not follow the trend of observation data very well). Hence, it should be explored whether the grouping criteria for the major groups could be applied to subgroups or not. Fourthly, in this study, only the ratio of the mean precipitations is considered because the data is to be applied for water resources management such as reservoir operations. If other statistical moments (e.g., variance, skewness, …) should be considered, the problem would become more complex and MCDM (Multiple-criteria decision-making) may be needed. Finally, with more studies in different climates around the world, a problem to be resolved is to find patterns on bias correction boundaries and number of groups.

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Reference

Bates B, Kundzewicz ZW, Wu S, Palutikof J. 2008. Climate change and water. Intergovernmental Panel on Climate Change (IPCC).

Block PJ, Souza Filho FA, Sun L, Kwon HH. 2009. A Streamflow Forecasting Framework using Multiple Climate and Hydrological Models1. JAWRA Journal of the American Water Resources Association, **45**: 828-843.

Chen J, Brissette FP, Leconte R. 2011. Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. Journal of Hydrology, **401**: 190-202.

Chen J, Brissette FP, Poulin A, Leconte R. 2011. Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed. Water Resour Res, **47**.

Christensen JH, Boberg F, Christensen OB, Lucas-Picher P. 2008. On the need for bias correction of regional climate change projections of temperature and precipitation. Geophys Res Lett, **35**.

Compagnucci R, Da Cunha L, Hanaki K, Howe C, Mailu G, Shiklomanov I, Stakhiv E. 2001. Hydrology and water resources. Climate change: 191-233.

Déqué M, Rowell D, Lüthi D, Giorgi F, Christensen J, Rockel B, Jacob D, Kjellström E, De Castro M, van den Hurk B. 2007. An intercomparison of regional climate simulations for Europe: assessing uncertainties in model projections. Climatic Change, **81**: 53-70.

Fowler H, Blenkinsop S, Tebaldi C. 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. Int J Climatol, **27**: 1547-1578.

Fung F, Lopez A, New M. 2011. Modelling the impact of climate change on water resources. Wiley Online Library.

Hansen JW, Challinor A, Ines AVM, Wheeler T, Moron V. 2006. Translating climate forecasts into agricultural terms: advances and challenges. Climate Research, **33**: 27-41.

Ines AV, Hansen JW. 2006. Bias correction of daily GCM rainfall for crop simulation studies. Agricultural and forest meteorology, **138**: 44-53.

Johnson F, Sharma A. 2011. Accounting for interannual variability: A comparison of options for water resources climate change impact assessments. Water Resour Res, **47**.

Leander R, Buishand TA. 2007. Resampling of regional climate model output for the simulation of extreme river flows. Journal of Hydrology, **332**: 487-496.

Leander R, Buishand TA, van den Hurk BJ, de Wit MJ. 2008. Estimated changes in flood quantiles of the river Meuse from resampling of regional climate model output. Journal of Hydrology, **351**: 331-343.

Lenderink G, Buishand A, Deursen Wv. 2007. Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. Hydrology and Earth System Sciences, **11**: 1145-1159.

Murphy J, Sexton D, Jenkins G, Boorman P, Booth B, Brown K, Clark R, Collins M, Harris G, Kendon E. 2009. UKCP09 Climate change projections. ISBN 978-1-906360-02-3.

Piani C, Haerter J, Coppola E. 2010. Statistical bias correction for daily precipitation in regional climate models over Europe. Theoretical and Applied Climatology, **99**: 187-192.

Qin D, Manning M, Chen Z, Marquis M, Averyt K, Tignor M, Miller H. 2007. Climate change 2007: the physical science basis. Contribution of Working Group I to the Fourth Assessment

Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, New York, NY, USA, **996**.
Schmidli J, Frei C, Vidale PL. 2006. Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods. Int J Climatol, **26**: 679-689.
Sharma D, Das Gupta A, Babel M. 2007. Spatial disaggregation of bias-corrected GCM precipitation for improved hydrologic simulation: Ping River Basin, Thailand. Hydrology and Earth System Sciences, **11**: 1373-1390.
Sun F, Roderick ML, Lim WH, Farquhar GD. 2011. Hydroclimatic projections for the Murray-Darling Basin based on an ensemble derived from Intergovernmental Panel on Climate Change AR4 climate models. Water Resour Res, **47**.
Terink W, Hurkmans R, Torfs P, Uijlenhoet R. 2009. Bias correction of temperature and precipitation data for regional climate model application to the Rhine basin. Hydrology and Earth System Sciences Discussions, **6**: 5377-5413.
Teutschbein C, Seibert J. 2010. Regional climate models for hydrological impact studies at the catchment scale: a review of recent modeling strategies. Geography Compass, **4**: 834-860.
Teutschbein C, Seibert J. 2012. Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. Journal of Hydrology, **456**: 12-29.
Wilks DS. 1990. Maximum likelihood estimation for the gamma distribution using data containing zeros. J Climate, **3**: 1495-1501.

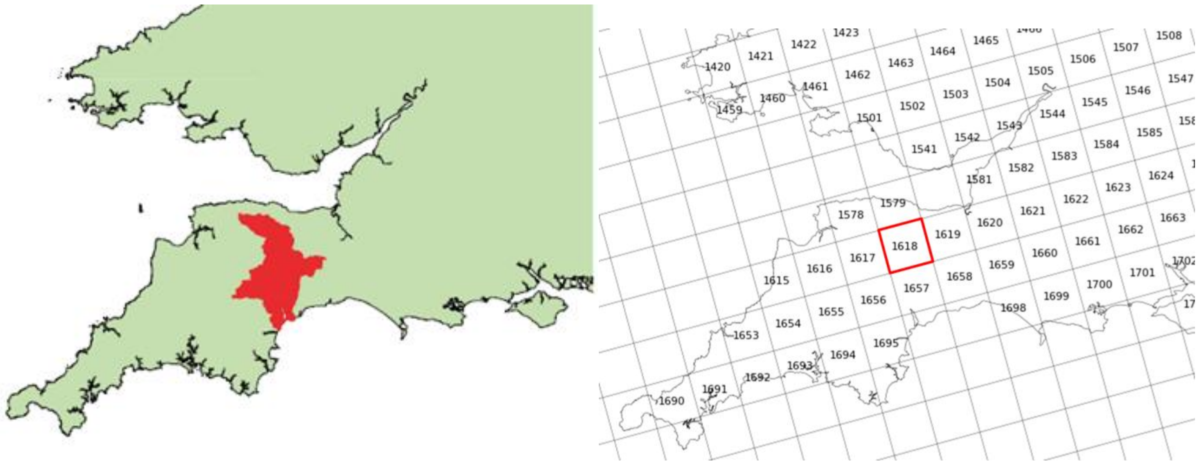

Figure 1. Location of the Exe catchment (left) and HadRM3 25km grid boxes (right). The Thorverton catchment is located in the highlighted grid box.

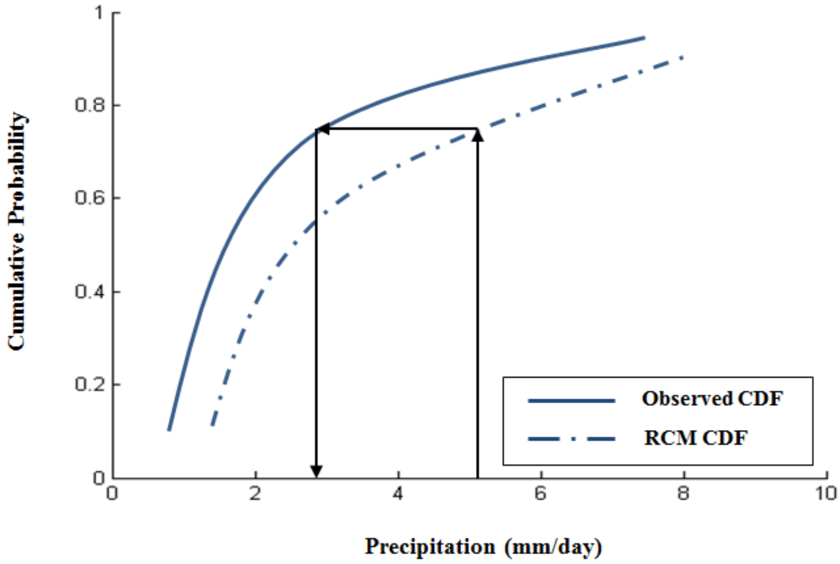

Figure 2. Schematic of distribution mapping: Distribution function of the RCM simulated data is shifted to the distribution function of the observed data.

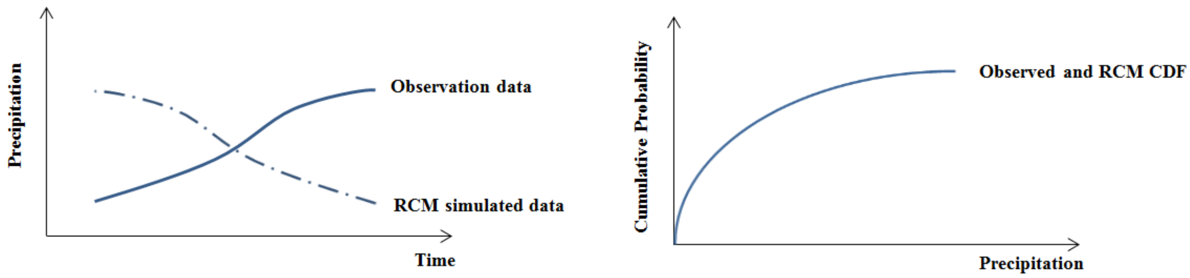

Figure 3. Illustration of time series of the observation data and RCM simulated data which are symmetrical in time (left) and cumulative distribution function of these symmetrical time series data (right).

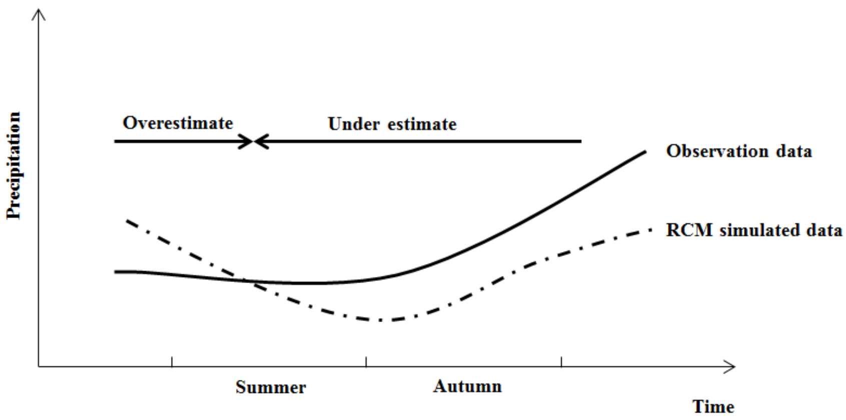

Figure 4. Illustration of the drawback of the calendar based (seasonal) bias correction. Dividing the correction period on seasonal basis breaks rainfall characteristics. In the summer both overestimation and underestimation of the observed trend coexist.

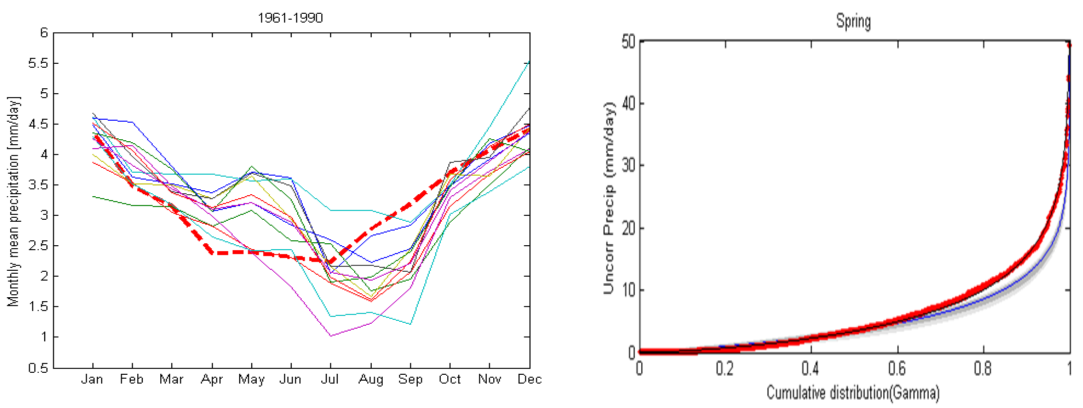

Figure 5. Comparison between the observed and RCM simulated data. *Left*: Monthly mean precipitation for 30 years from 1961 to 1990. The red dashed line is the observation data line and the solid lines are ensembles of 11-member output. *Right*: Gamma distribution of the observations (red) and Gamma distributions of RCM simulated data (gray shaded area).

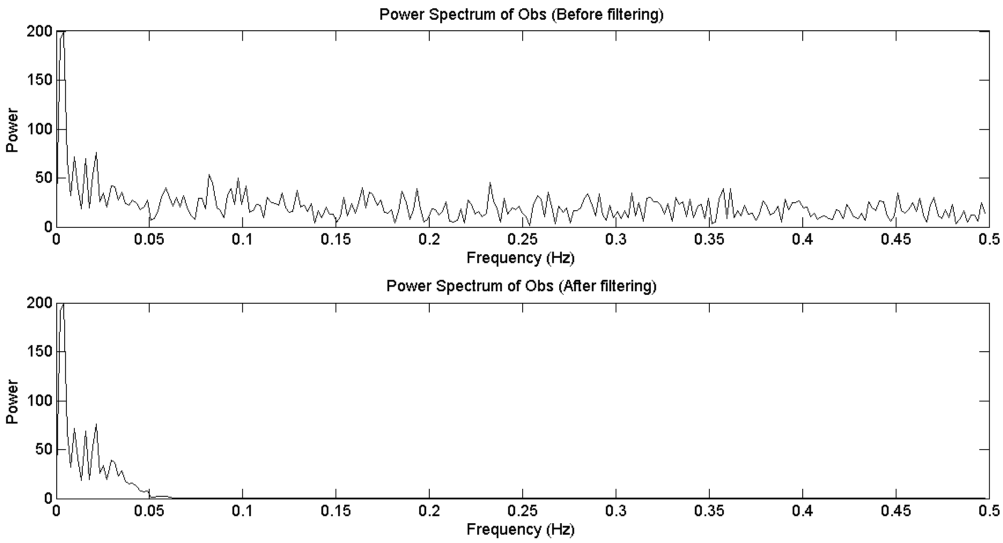

Figure 6. Power spectrum of the observed precipitation data before and after cut-off.

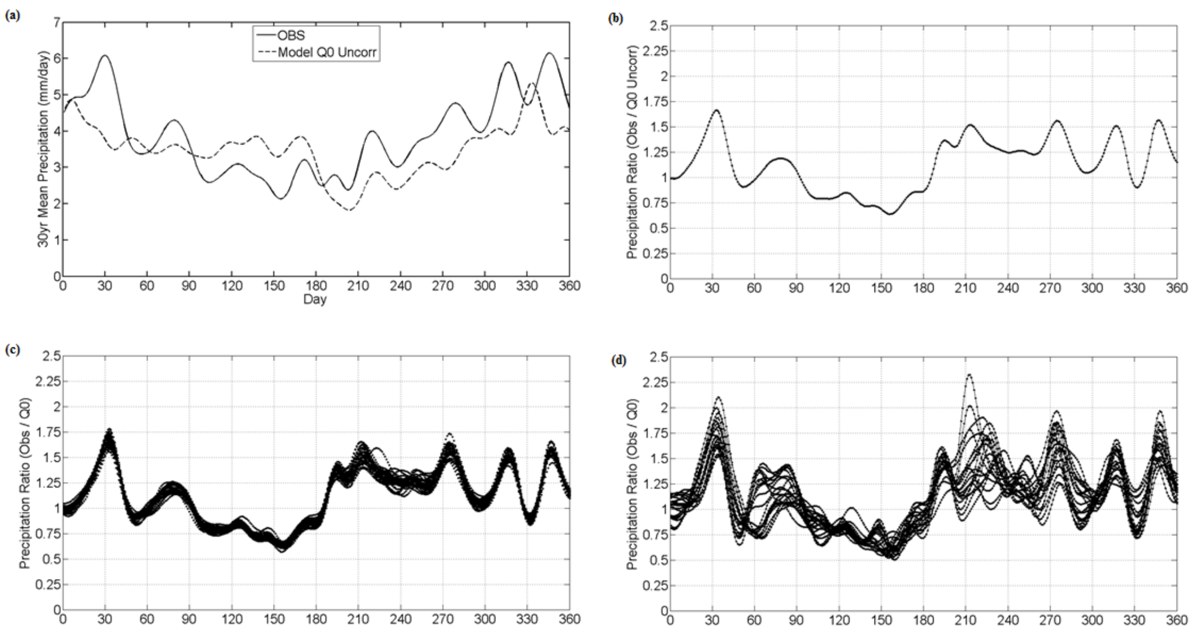

Figure 7. (a) Signal of the observation (red) and RCM simulated (blue) data after filtering; (b), (c), (d) illustrate the 30-year mean precipitation ratio, ensembles of 29-year and 20-year mean precipitation ratios respectively.

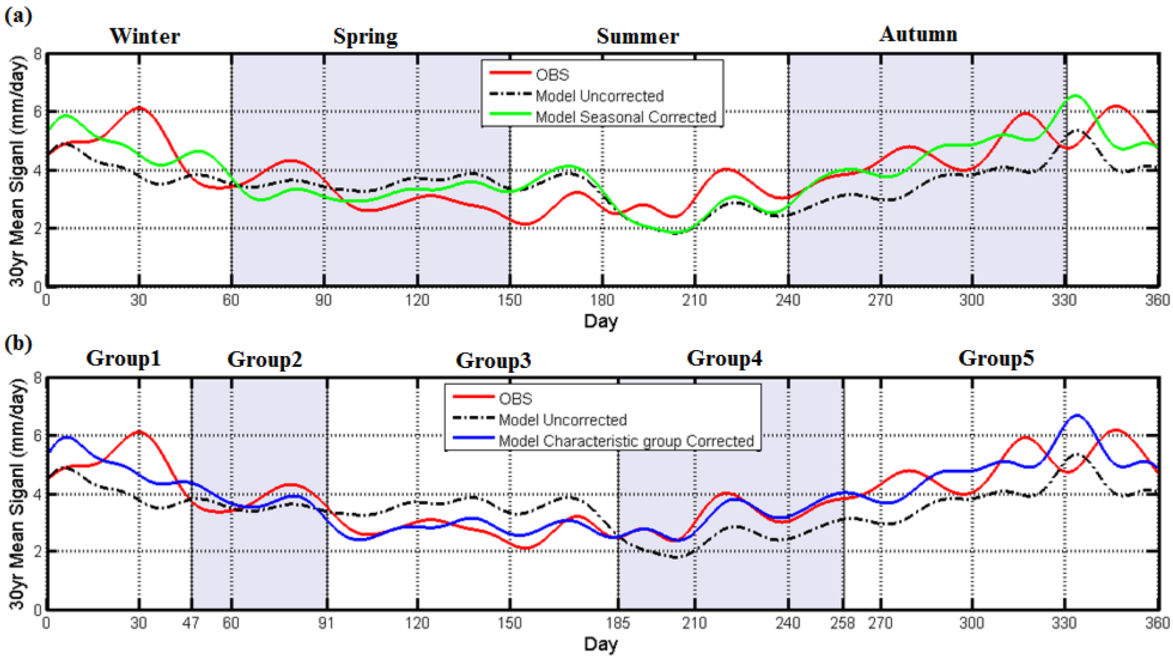

Figure 8. Comparison of proposed bias correction method and conventional method.